Reinforcement Learning 2

Complications & approximations

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Psych 209, Winter 2018

Introduction

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Talk about all the stuff that makes it messy:



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- Infinite spaces & approximations.
- Correlations & replay.
- Exploration & on/off-policy learning.
- Unobservables & POMDPs, different assumptions and other approaches.

Function approximation

Similarities & dissimilarities

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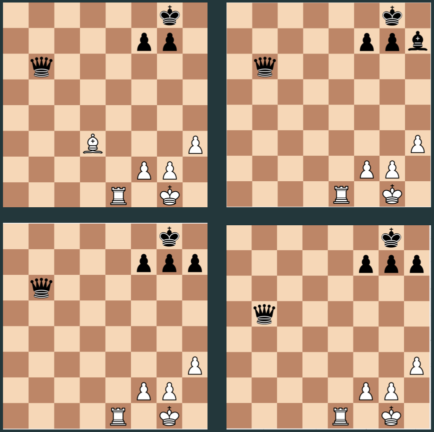
- However…



Approximating the Q-table

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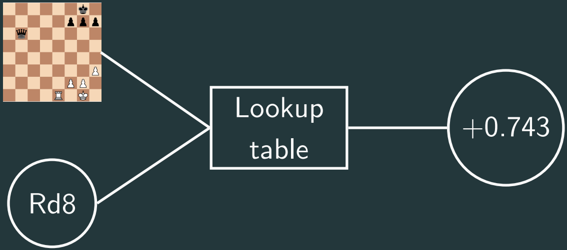

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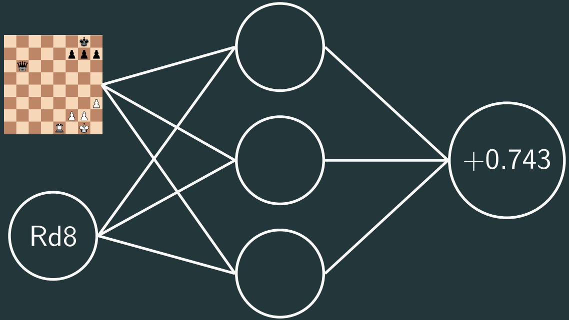

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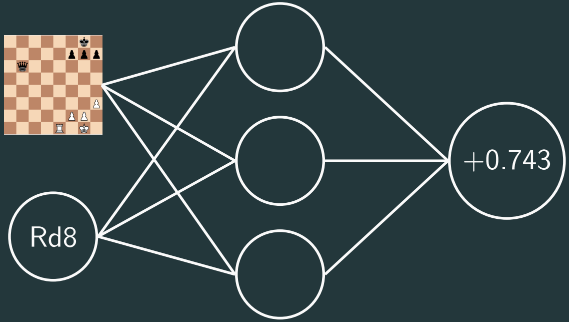
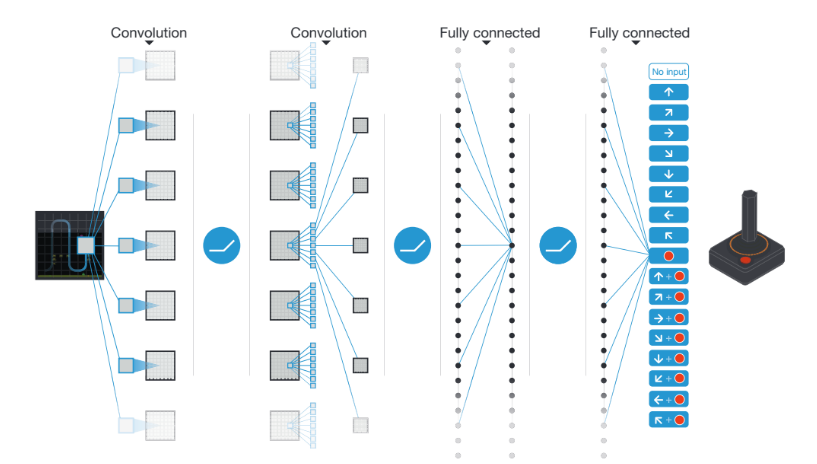


- Loss:

$$L = \left(r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a'; \theta_i^-) - Q(s_t, a_t; \theta_i) \right)^2$$

Playing atari games



Replay

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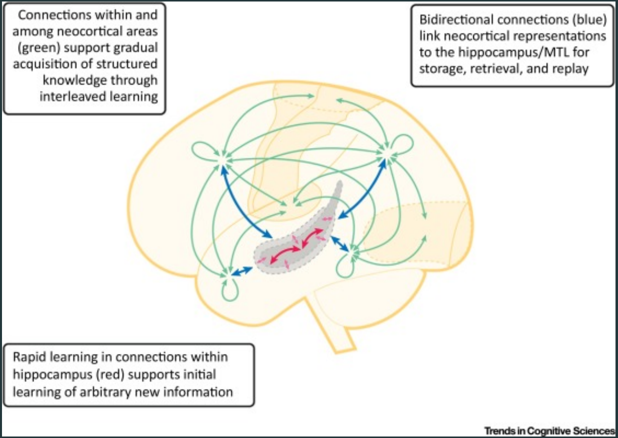
- CLS is a theory of how humans and animals avoid this:



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$$\Delta Q^\pi(s_t, a_t) = \alpha \underbrace{\left(\left[r_{t+1} + \max_{a'} \gamma Q^\pi(s_{t+1}, a')\right] - Q(s_t, a_t)\right)}_{\text{prediction error!}}$$

  we sample a random experience from our buffer and update with that: $k \sim \mathit{Unif}$(replay buffer indices)

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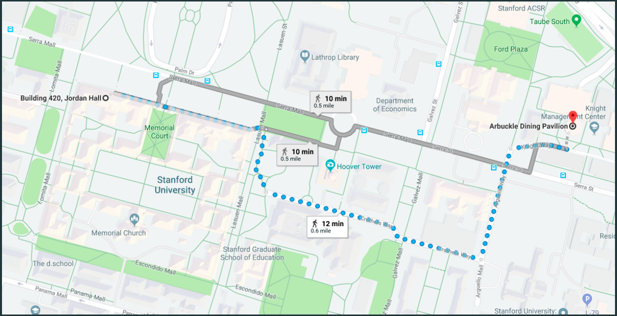
Exploration and exploitation and on/off policy

The need to explore



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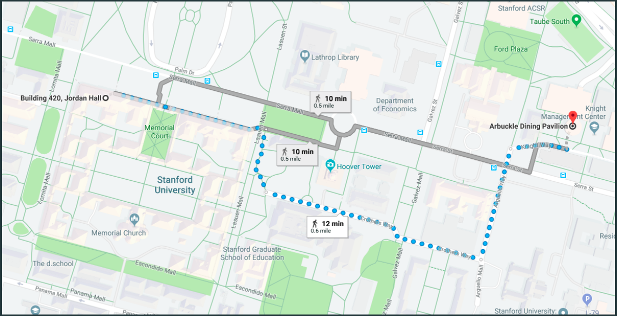

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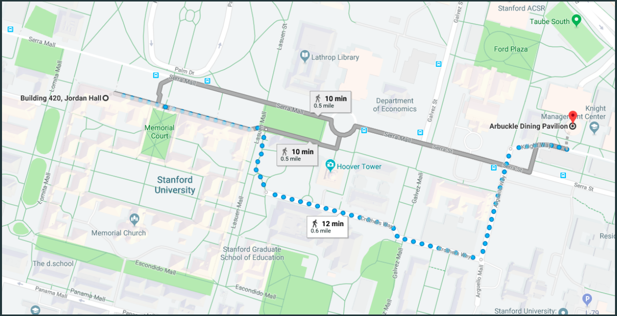

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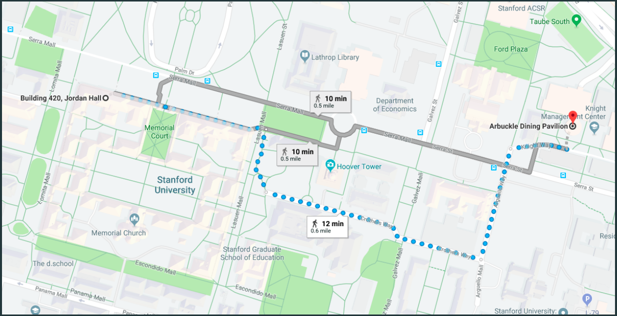

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- This is important – remember convergence guarantees required *every* state, action pair to be visited "frequently."

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- Exploiting risks missing a great opportunity.
- We have to find some balance between these that results in good payoffs but still makes sure we don't miss too much.

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- We can also do clever things like *anneal* ϵ over training.
    - Act mostly randomly and explore a lot early in training.
    - Act mostly greedily and exploit a lot late in training/in testing.

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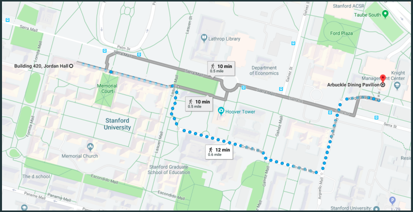
- Do chess players stop learning when they're playing for the world championship?
- A self-driving car can't just be trained and set free – destinations, roads, and laws are all evolving.
- What if my direct path to lunch was blocked by a building that was torn down?



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- If we want to behave optimally with a policy π that explores, we have to incorporate this policy into the learning rule:

$$\Delta Q^\pi(s_t, a_t) \stackrel{?}{=} \alpha\left(\left[r_{t+1} + \sum_{a'} p(a'|s_t, a_t, s_{t+1}, \pi)\, \gamma Q^\pi(s_{t+1}, a')\right] - Q(s_t, a_t)\right)$$

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- Since our actions in the state are distributed according to π, in expectation our Q-value updates will be as well.

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- **Off-policy:** Can learn from anything, even totally random play – incorporating more early exploration or replay easier.

Wrapping up

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- There's a trade-off between **exploring** and **exploiting**!
- … and there's way more to RL than will fit on one slide or one course.

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- ... Or something in between? (Successor-representation, imagination.)
- And much more.